Exploring the Practical Level of Application with the AI-enabled Social Media Data: A Case Study of Hurricane Harvey in 2017

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Abstract

Locating an emergency event is critical in situation awareness and for rescue operations during natural disasters. As an emerging data source, Twitter provides wide and continuous coverage of the field with rich information containing texts and images. However, extracting precise locations of particular tweets is challenging because the GPS information of the tweets is usually unavailable. Here we present a new data mining strategy to address this issue. A deep learning based natural language processing model is applied to recognizing location names from the textual content of tweets. The coordinates of the recognized location names are determined by searching a local gazetteer built based on the GeoNames gazetteer and the road data from the US Census. Meanwhile, images that reflect the field situation are identified and classified with a computer vision model. Combining text analysis and image recognition, we capture the tweets that contain field images and detailed locations to fully understand the situation on the ground. Two applications are demonstrated by hand picking after the automatic processing. The AI-enabled social media data is shown useful for understanding the phase transition of the disaster event, enhancing the situation awareness through collecting the first-hand disaster witness, and providing a passive hotline for rescue and search activities. The present study

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demonstrates an innovative approach to capturing valuable information from a real-time data source for emergency response.

Keywords: Computer Vision, Natural Language Processing, Convolutional Neural Networks, Pluvial Flooding, Social Media

1. Introduction

Urban flooding is becoming a national threat, causing billions of dollars of losses every year. Urban flooding can be attributed to compounding causes with the continuing threats of riverine and coastal floods and the rise of pluvial (flooding due to overwhelm precipitation) and nuisance (flooding due to sea-level rise, also called "sunny day flooding") floods (Galloway et al., 2018; Rosenzweig et al., 2018; Moftakhari et al., 2018). Different from the traditional water basin-scale flood analysis, analyzing and predicting urban floods requires data with high spatial and temporal resolution, but collecting high quality geotagged urban flooding data is challenging, because the traditional method is limited. For example, remote sensing is difficult in signal processing and limited in weather condition such as cloud coverage; sensor networks are expensive to install and maintain in urban areas; insurance reports are usually inaccessible and delayed in time; and government surveys usually are limited in coverage (Wang et al., 2018a).

Crowdsourcing or citizen science methods emerged as an innovative solution to address this data challenge for urban flooding. In general, two types of data can be collected through social media such as Twitter: texts and images. Texts were used in the early study of Jongman et al. (2015), who analyzed the texts of flood-related tweets from disaster response organizations and used the information of near-real-time to understand the locations, the timing, the causes, and the impacts of floods. They found tweets combined with satellite data can reasonably outline the affected location, provide one to several days of early warning, and detect unexpected or controversial flood events such as dam breaking. Photo images were used by Laney (2001), who collected photos from social media posts to estimate the water extent and depth. They developed a tool of "PostDistiller" to filter geolocated posts from social media services that include links to photos and manually remove the irrelevant posts. The developed method was applied to the June 2013 flood event in Dresden, Germany. A recent study of Huang et al. (2019) was designed to combine texts and photos for data fusion and improved flood estimate. A more complete survey of the crowdsourcing/citizen science studies can be found in Zheng et al. (2018) and See (2019). They reviewed crowdsourcing-based data acquisition methods that have been used in a broad spectrum, covering seven domains of geophysics including weather, precipitation, air pollution, geography, ecology, surface water, and natural hazard management. They summarized the advances in the use of citizen science and crowdsourcing data can benefit the flood monitoring practice.

Using social media data has several advantages over traditional data collection. Social media data provides a wide and continuous coverage with high resolution. This data source is also much cost effective. A typical social survey at the city level usually requires years of dedicated investment of resources to be successful (Savage et al., 2013). However, social media data is able to capture household level snapshots about human society with limited resource dedication (Huang & Xu, 2014). Moreover, the timing of transitions is not clear between various disaster management phases so that the onsite management do not always follow the transition timely (Warfield, 2008). Social media data provides real-time information for the emergency managers to quickly access the evolution and transition situations of the disasters to support informed decision-making through multiple phases of disaster management.

Although social media streaming allows *real-time* data to be downloaded and stored, extracting information from the stream in *real-time* is challenging, which needs a rapid processing capability to deal with the high volume, fast velocity, and strong heterogeneity (variety) – the 3 V's in big data (Laney, 2001). Early studies that processed social media data manually cannot meet this *real-time* requirement, because the manual method is slow, costly, and subject to inconsistency caused by human subjective judgment, decreasing concentration, and emotional fluctuation. Artificial Intelligence (AI) methods were therefore introduced to automatize the data processing tasks. Wang et al. (2018a) created a new method using AI to automatize the process, in which Natural Language Processing (NLP) techniques are applied to the data collected from Twitter. They used topic modeling to filter the relevant topics and Named Entity Recognition (NER) to extract the flood location information. They found social media based flood monitoring can complement the existing means of flood data collection and the validation against precipitation data showed a good correlation. Asmai et al. (2019) conducted a more general study. They used a topic modeling approach of Term Frequency-Inverse Document Frequency (TF-IDF) to automatically filter the flooding topic, but the location names were not extracted. Huang et al. (2019) developed an automated flood tweets extraction approach by mining both visual and textual information. They trained a Convolutional Neural Network (CNN, an AI-based classification algorithm) model to classify the visual content of flood pictures. They applied the method to a flood event in Houston and found that coupling CNN classification of pictures and key words in tweet texts can enhance the accuracy without sacrificing the recall rate to discriminate flood topics from others. The application of AI methods in flood observation is still in its infancy and has great potential to become a major data source, especially in the situations that flood monitoring infrastructure is underdeveloped (Wang, 2020).

One important type of information that AI can help extract from social media, such as tweets, is geographic location. During flooding events, locations are frequently mentioned in social media messages. Accurately extracting locations from them can help understand the emergency situation on the ground. It is worth differentiating the geographic locations tagged to social media messages (i.e., geotagging) and those locations mentioned within the message content. MacEachren et al. (2011) considered these two types of locations as *tweet-from* locations and *tweet-about* locations. While *tweet-from* locations are usually in a structured format of longitude and latitude, *tweet-about* locations are embedded in natural language texts and can be difficult to extract. *Geoparsing* is the process of recognizing place names, or toponyms, from texts and identifying their corresponding locations (Freire et al., 2011; Gelernter & Balaji, 2013; Gritta et al., 2018). A number of geoparsing tools, or *geoparsers*, have been developed, such as GeoTxt (Karimzadeh et al., 2019) and TopoCluster (DeLozier et al., 2015). However, existing geoparsers often use a traditional machine learning model, such as Conditional Random Field (CRF), for recognizing locations from texts, and there is limited research on applying deep learning models for extracting locations from social media.

Emergency management typically consists of four phases: mitigation, preparedness, response, and recovery. Researchers have developed various lists to categorize social media data. For example, Vieweg (2012) coded social media messages into "Caution, Advice, Fatality, Injury, Offers of Help, Missing, and General Population Information" and Imran et al. (2013) categorized into "caution and advice, casualty and damage, donation and offer, and information source". A remarkable work has been conducted by Huang & Xu (2014), who developed an innovative framework to classify social media data into stages following the disaster management schemes including preparedness, emergency response, and recovery. Note that the category "mitigation" was not used because it is related to long term activities and does not reflect the *real-time* change of social media data. They manually examined more than 10,000 tweets from a natural disaster and employed a classifier based on logistic regression. To our knowledge, such detailed classification has not been created for image data streamed from social media. Since image data contains much richer information and higher credibility than texts, creating such an image classifier could greatly benefit the disaster management and the present study is designed to fill the gap.

The present study is targeted to further the development of AI's application in flood observation by combining Computer Vision (CV) and NLP techniques for information extraction from social media. The major contribution and novelty of the paper are: 1) an original framework is developed that uses the texts of tweets to locate the event and uses the photo images to infer temporal-spatial information related to a disaster. 2) This study is the first attempt of using AI to classify the photo images from social media into four categories – impact, preparedness, emergency response, and recovery – which has been used among disaster researchers and can benefit emergency managers to organize information and prioritize activities during a disaster. 3) The developed framework is applied to a flood event of Hurricane Harvey in the Houston area in 2017. This case provides us with a testing bed to explore the best use of social media data for flooding related research. Different from Huang et al. (2019), our study focuses on geolocating tweets related to flooding at a street-level resolution and our four-category classification provides more detailed information than their flood/no-flood binary classification.

2. Method

A Twitter dataset for Hurricane Harvey (Phillips, 2017) was obtained through the North Texas Library. The dataset was collected using a comprehensive keyword list from Twitter covering the period of August 18, 2017 to September 22, 2017. The dataset contains a total of 7,041,794 tweets and retweets and the total file size is 43.2 GB in the format of JSON. Of the total original tweets, only 7537 are geo-tagged (Yang et al., 2019).

Hurricane Harvey was a Category 4 storm. It started on August 17, 2017 and ended on September 2, 2017, with a landfall on Texas and Louisiana. The caused $125 billion of catastrophic flooding and many deaths were tied with 2005's Hurricane Katrina as the costliest tropical cyclone on record (National Hurricane Center, 2018). Many affected areas recorded more than 40 inches of precipitation, ranking Harvey the wettest tropical cyclone in the recorded history of the United States.

An innovative framework is developed to extract information from the Hurricane Harvey tweets (see Figure 1). It consists of two routes of data processing: texts and photos. In processing texts, our method runs in two steps: (1) toponym (or place name) recognition and (2) toponym resolution. For toponym recognition, we use a deep learning based named entity recognition tool, NeuroNER (Dernoncourt et al., 2017a), which trains a long short-term memory (LSTM) model which is a variant of the recurrent neural network based on the CoNLL 2003 dataset. It has been shown that neural network based models generally outperform traditional models such as CRF in the task of NER (Collobert et al., 2011; Dernoncourt et al., 2017b). Step (1) recognizes place names mentioned in tweets such as "Houston" and "Solomon Rd", while step (2) assigns geographic coordinates to the recognized place names. GeoNames is the most comprehensive gazetteer which contains over 25 million place names throughout the world. However, GeoNames primarily covers city and town names, and does not contain detailed information about roads whose names are also mentioned in social media. Therefore, we make use of the TIGER data from the US Census which provide the most authoritative road network data in the United States. Currently, we include all the roads from Harris county, a county that covers most parts of the city of Houston. The recognized place names are located to the center of a city (e.g., "Houston") or the center of a road segment (e.g., "Solomon Rd"). GeoNames and TIGER road data are downloaded and organized in a local PostgreSQL database with PostGIS extension. Spatial indexing is enabled to speed up the geolocating process.

In processing images, we develop a TensorFlow based automatic flood categorizing scheme that can be used to extract various information from social media images. Two deep learning architectures were adopted to classify the images, including Convolutional Neural Networks (CNN) and Residual Neural Networks (ResNet). The CNN (also known as ConvNet) is composed of a group of layers based on their functionality: Convolutional Layer, Pooling Layer, and Fully-Connected Layer. ResNet is a Neural Networks scheme that allows skips of layers in the network structure. The present study used the CNN and ResNet v2 architecture developed in Gulli & Pal (2017) with data augmentation to perform the picture classification. The selected data augmentation techniques were re-scaling, rotation, horizontal shifting, zooming, and flipping. Keras (Gulli & Pal, 2017), a Python-based deep learning code, was implemented, which was run

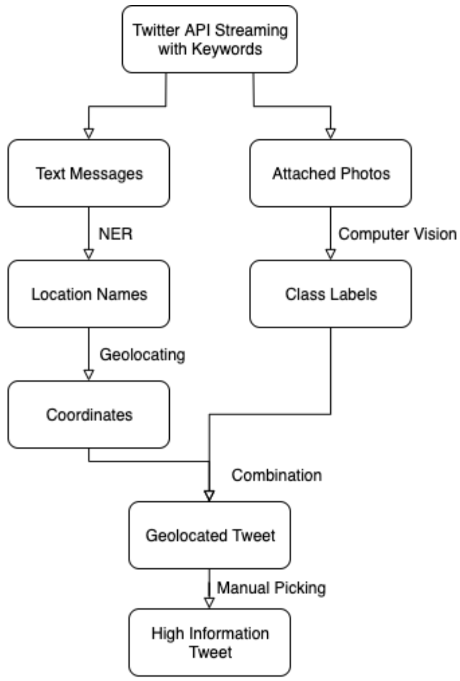

Figure 1: Data processing flowchart.

with CUDA libraries on the GPUs (Graphics Processing Units) of the computer cluster hosted at the School of Engineering, Rutgers University.

The CV based classification algorithm was applied to a new categorizing scheme for social media image data to support the understanding of the phase transition in the stream of social media data and to inform the decision makers about the phase transitions. Following the four phases of the disaster management (Huang & Xu, 2014), we decide to categorize the images into four classes – preparedness, impact, response, and recovery. Similar to Huang & Xu (2014), "mitigation" is not used to label images because it refers to the long-term activities that cannot be appropriately identified in the course of disasters. We separate the "impact" category from the general "response" to capture the first-hand onsite witness evidence, because we are interested in extracting the information of high-resolution geolocations and the direct witness evidence that is more valuable in flood monitoring. Different from text categories where keywords can be used to describe each category, we rely on a more flexible and empirical protocol to classify the images. In general, we follow the following rules in labeling the training dataset:

(a) **Impact**: the onsite first-hand witness of the flood scene, which provides the valuable social-media-only information.

(b) **Preparedness**: the warnings of flood development, preparedness tips, and forwarded weather forecasts.

(c) **Recovery**: the activities about rebuilding the community and removing the solid wastes.

(d) **Response**: forwarded media reports about flood events and rescue activities.

We randomly selected 6542 images to prepare a training dataset, in which the impact, preparedness, recovery, and response categories contain 4617, 772, 79 and 1074 images respectively. The sample images are shown in Figure 2.

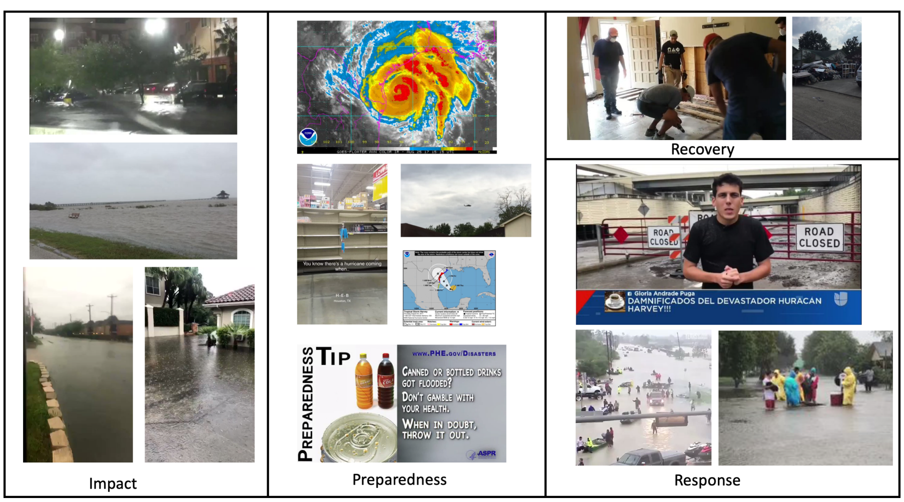

Figure 2: Sample classified images from each category.

After a deep learning training, the best CV model (specified in the result section) was selected to process all of the 151,979 images collected in the dataset. Then, the processed texts and image labels are merged to the same database.

The information is then filtered manually depending on the purpose of the task (specified in the result section).

The modeling results of HAND (Heigh Above Nearest Drainage) is downloaded from CUASHI (Consortium of Universities for the Advancement of Hydrologic Science, Inc. https://www.cuahsi.org/) (Liu et al., 2018). HAND is an approach to representing the relative elevation of a land surface cell above the cell in the river/stream to which it flows. This method is a digital terrain-based flow analysis that doesn't require detailed cross-sectional surveys (Tarboton, 1997; Tarboton & Baker, 2008). The flood event for Hurricane Harvey was simulated using this method and is compared with the Twitter data to explore the best use of social media data in disaster management.

3. Results

3.1. Computer Vision Training and Processing

Classical metrics are used to quantify the quality of image category classification: precision, recall and F1-score. Precision is the fraction of retrieved documents that are relevant to the query; Recall, used with precision, is the fraction of the relevant documents that are successfully retrieved; F1-score is a function of Precision and Recall to balance the two metrics, which is considered a more comprehensive measure of the data extraction performance. Their equations are shown below.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{1}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{2}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

Every image is rescaled to two different resolutions: 32×32 and 256×144 (144p). For different resolutions, we apply the metrics to cross-validate the performance of the CV processing with two different deep learning architectures – CNN and ResNet. The results are shown in Table 1.

Category	Resolution 32 × 32						Resolution 256 × 144					
	CNN			ResNet			CNN			ResNet		
	P	R	F	P	R	F	P	R	F	P	R	F
Impact	0.85	0.55	0.67	0.85	0.90	0.88	0.92	0.31	0.46	0.84	0.90	0.87
Preparedness	0.65	0.58	0.62	0.67	0.64	0.65	0.24	0.70	0.36	0.67	0.67	0.67
Recovery	0.01	0.07	0.02	0.03	0.02	0.02	0.00	0.00	0.00	0.14	0.13	0.13
Response	0.28	0.63	0.39	0.53	0.43	0.48	0.24	0.62	0.35	0.56	0.39	0.46

Table 1: Computer Vision performance (P: Precision; R: Recall; F: F1-Score).

In general, we cannot find significant difference in processing the two resolutions. This result is a little surprising, because the high resolution, which takes more memory and computation costs, is expected to outperform the lower. Regarding the different architectures, ResNet is generally better than CNN, which is an expected result as ResNet is more flexible. The best classification performance for the "Impact" category was found to be the ResNet at the 32×32 resolution scheme, which reaches the highest F1 score of 0.88. The reason can be attributed to the dominating number of training data. In contrast, the "Recovery" category has the worst results due to the low number of training set. Based on the analysis of Table 1, we can conclude that ResNet has the best performance in the resolution of 32×32, and therefore, we choose this model to process all the images streamed from Twitter.

3.2. Times series of the four categories

The CV model of ResNet is applied to classify the images into four categories. The total of 22,390 images are classified into: 12,829 "Impact" images, 5,064 "Preparedness" images, 43 "Recovery" images, and 4,454 "Response" images. The daily volume of tweets in the four categories is shown in Figure 3. The "Preparedness" category is found to peak on Aug 25 – 2 days ahead of the 'Impact" peak, and both of the "Recovery" and "Response" categories hit the maximums on Aug 29, which is 2 days later than the "Impact" category. The order of the peaks is consistent with the three phases of disaster management: preparedness, response, and recovery, so it proves that the scheme of the four-category classification is producing reliable results. The CV-classified daily volume clearly shows the phase transition, which can be generated in real-time and easy to access with the trained CV model. So there is a great potential to use this curve to inform the disaster managers about the development timely to improve their coordination and responding to the disaster emergencies.

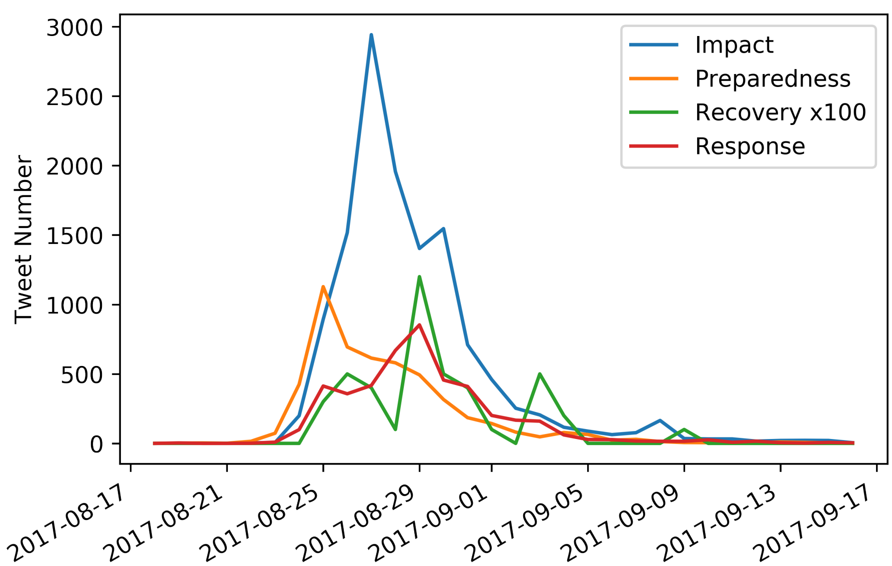

Figure 3: Daily tweet volume for four categories.

3.3. Spatial distribution of geolocated tweets

The daily spatial distribution of geolocated tweets from Aug 28 to Sep 3, 2017 is shown in Figure 4. The text-based geolocated tweets, which are represented by the white dots, concentrate in the urban area. The tweets with images are a small portion of the total volume and sparsely distributed over the city area. Similar patterns can be found in each of the four categories. Furthermore, the "impact" tweets were observed to place closer to major roads than other categories. Note that the "Recovery" category tweets are ignored in this map due to its extremely low number compared to others.

The tweets geolocation results are compared with the flood extent data produced by the HAND model (Liu et al., 2018). The results show that the tweets distribute generally randomly and uniformly in the city except the flood patches, e.g. the Addicks-Barker Reservoir area. We didn't find any correlation between the tweet distribution and the flood development through visual examinations.

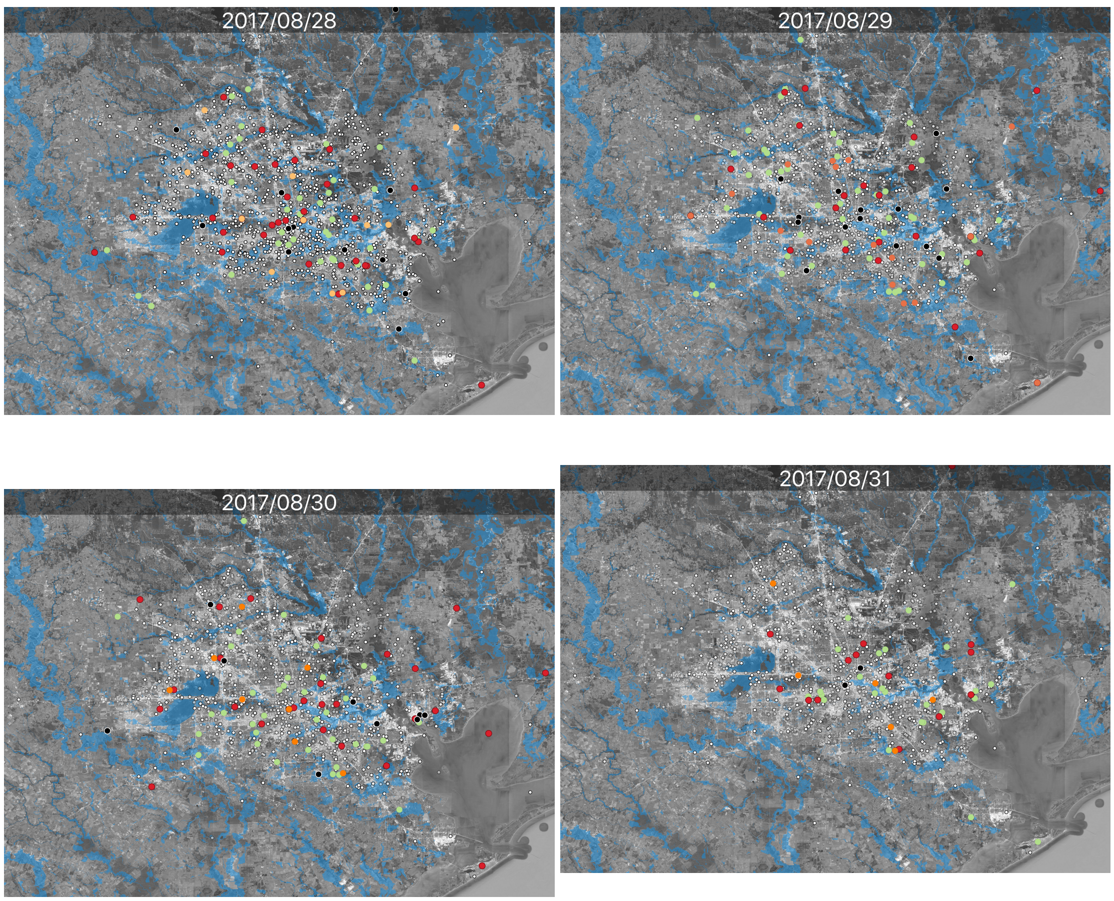

Figure 4: Spatial distribution of geolocated tweets with a comparison of HAND model (white: geolocated tweets; green: tweets with images; red: tweets in category "Impact"; black: tweets in category "Preparedness"; orange: tweets in category "Response"; and blue block: flood extent predicted by HAND

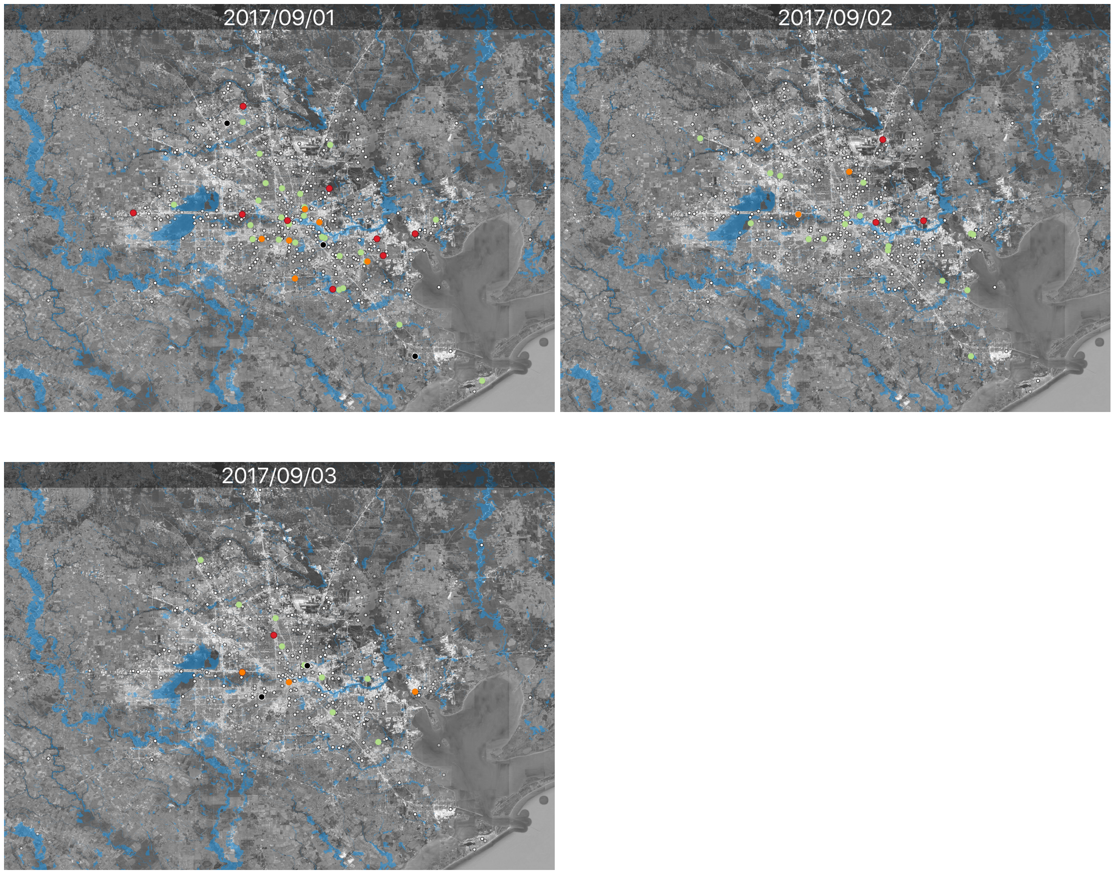

Figure 4: Spatial distribution of geolocated tweets with a comparison of HAND model (Cont.)

3.4. Manual Information Extraction

The automatic classification established a rapid topic filtering framework for the noisy and high volume social media data, which provides a classified and focused database for further use. Given the uncertainty in the AI algorithms, we note that manual data mining is still necessary in many cases. Here we develop two examples to demonstrate that manual information extraction can be used to refine the filtered dataset and add high values for practical application.

The first demonstration is targeted to collect onsite, first-hand flood scene information. In the demonstration, the pool of images are automatically filtered using the CV classification as the "PostDistiller" and then manually picked from the "Impact" category to shrink the dataset to 698 high-value images. The procedure is similar to the manual examination in Fohringer et al. (2015) except that the "PostDistiller" is a deep-learning filter here. The hand picked dataset captured the onsite situation with the first hand witness evidence of the field that can be used to create lively understanding of the real-time situation of the field. The filtered dataset also highlights a series of issues that official media often ignored. For example, from the dataset, we find visual witness of flooding in nursing houses, flood trapped animals (e.g. horses, dogs), unusual animal presence in the city such as crocodiles, snakes, and fire-ants, the emergency of fountaining sewer manholes, road damages, and indoor floods. These issues are usually not priority in disaster management but could be significant to complement the information for situation awareness and the completeness of disaster emergency responses. The hand picked dataset is also meaningful to enrich and broaden the flood information in general, because it adds an additional "orthogonal" dimension to the conventional data sources from the perspective of information theory.

The second demonstration is targeted to identify the tweets with street-level resolution of geolocation and first-hand onsite witness photos that are different from official media. These photos are provided by unprofessional Twitter users who captured the local situation that can contribute "orthogonal" dimension to the mainstream data of the official agencies such as FEMA and NOAA and professional media such as local TV stations and newspapers. To achieve the goal, the place names recognized from tweets are compared with the local collection of city and town names. The tweets with place names different from the state, city and town names are collected. Then, the photos attached to these tweets labeled by the "Impact" category are examined manually to spot the highest value tweets. From the dataset of Hurricane Harvey, we identified 13 tweets that have the highest value and the samples are shown in Figure 5. These photos descriptions are shown useful for the emergency response team, because they have a high accuracy street-level location information to respond, e.g. rescue and search. So the method of information extraction in this demo – combining text-based geolocation, CV topic filtering, and human reading – is shown to have a great potential to create a passive "hotline" so that the onsite emergency messages can be notified of the emergency information to respond.

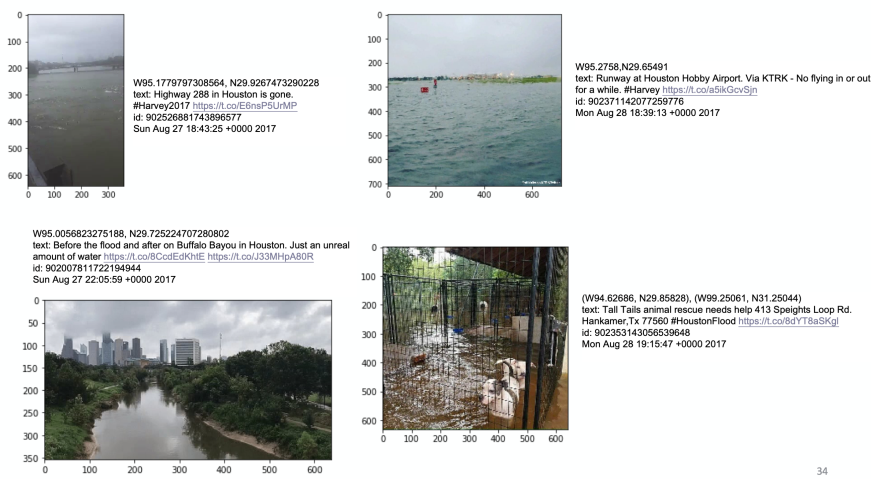

Figure 5: Sample of hand picked tweets with high geolocation accuracy and photo topic relevancy.

4. Discussion

4.1. What's the best use of AI-enabled social media data?

The present study uses the state-of-the-art deep learning methods for high accuracy data mining. The AI-enabled data processing framework provides rich information with high "orthogonal" values extracted from a high-volume and fast-updating data source to complement official data sources. However, compared to the conventional flood data sources, AI-enabled social media data processing is still struggling to address the issue of relatively high uncertainty. A key question arises: what's the best use of the AI-enabled social media data for flooding mitigation? The present study identifies three promising applications by creating the four-category photo classification and text and NER-based geolocation: 1) phase transition information for disaster management and coordination, 2) onsite witness collection for additional dimension of situation awareness, and 3) passive hotline for emergency rescue and search activities. The review papers (e.g. Zheng et al. (2018)) mentioned other directions of applications. Here we plan to comment on some of the aspects with the new insights gained through this study.

First, the passive hotline is a promising direction that AI-enabled social media data may reach the level of practical application. As indicated in the past studies that social media data is the most useful for emergency detection, AI technology can enhance the accuracy in capturing, geolocating, and classifying the social media data and thus enhance the level of practice. With the customized photo classification method (with the probability of coupling the text classification such as shown in Huang & Xu (2014)), there is a hope to reach a high accuracy of topic filtering to meet specific and practical information demand. This new framework will not only reduce the cost and time of manual social media analysis but also enhance the quality of the captured data.

Second, the AI-enable social media data shows a good reflection of the general trend thanks to the relatively high time accuracy and the large data volume. The customized photo and text classification can significantly improve the resolution of the trend analysis. For example, if only the preparedness information is interested, the framework can be customized to only capture its daily volume. The relative mature methods of topic clustering ensures the application level of accuracy and thus is expected to be promising in the future. Also, if only coarse resolution of the data is required such as at the city or state level, the AI-enabled processing can also deliver a satisfying result.

Third, AI-enabled social media data is still not practical to support the tasks of numerical modeling calibration and validation as the major data source. As social media has the benefits of wide coverage and continuous monitoring, there is a hope to use this unconventional data source mainly to calibrate and validate flood models (e.g. Wang et al. (2018a)). However, given the relatively high uncertainty and challenges in the completeness and accuracy in geolocating, we would note that the task is still too challenging with the frontier AI technology. In addition, social media data is only a biased sample of the social activities, so the task is almost impossible in nature. This problem is even worse as the data privacy issue is becoming more tight. A remarkable event is the recent announcement from Twitter that the service of high-accuracy GPS geo-tagging is suspended (Hu & Wang, 2020). Several potential means to mitigate the impact has been discussed therein and a thorough discussion on the privacy-related issues is beyond the scope of the present study.

4.2. What's the future research direction with AI-enabled social media data?

AI is a fast-developing field and every year there are numerous new models for improved data mining performance. We expect that new AI techniques will improve the level of accuracy for successful application in the near future. In addition to the AI technique advances, we would share our thoughts on a few other directions that could further the AI-enabled flood applications.

First, data fusion that combines social media, remote sensing and other data sources is considered to be an emerging research opportunity to provide quality data product for flood management. This data fusion techniques takes the advantage of each data source to create a more complete survey, which is possible to address data quality and accuracy problems and to support model validation and calibration tasks that the traditional methods fail. An effort has been made in the literature, i.e. Wang et al. (2018b).

Second, there is a big gap in using the social media data for data assimilation in real-time operation forecasting models. The rich information coming from social media could provide a new lively and sensible picture to warn and inform the forecasting end users. For example, the real-time and first-hand witness photos could be pushed up through mobile phone apps to enhance the situation awareness of the community at the risk.

Third, the data originated from social media is also valuable for training automatic systems. For example, smart infrastructure and automatic driving systems all need first-hand data to develop and improve their response. A customized AI filter can help developers to target and pick the most relevant data for training and testing.

Last but not least, misinformation can be included in social media stream and has been seen in the context of disasters (Abdullah et al., 2015). Such misinformation can mislead disaster response efforts and waste limited resources by spreading rumors or creating panic situations. Accordingly, we also need methods that can automatically detect fake and spam social media messages (Rajdev & Lee, 2015). Those methods can then be integrated with information extraction models to form a complete pipeline that derives true and actionable knowledge from social media.

5. Conclusion

The present study develops an original framework for flood data mining and processing from the social media platform Twitter. The framework consists of two tracks of data processing including the NLP-based geolocating track and the CV-based image classification/topic filtering track. Both tracks use the state-of-the-art deep learning algorithms and reach a high level of performance. This study is innovative in using local gazetteer with the LSTM NER model to improve the text-based geolocating performance. This study is also the first time of image classification study following the phase transition of disaster management using CV. The training was shown reaching high F1 score. The photo-based social media stream shows clear phase transition which can be used for disaster management. This framework combining text-based geolocation and image-based topic filtering is shown reflective of the general phase transition trend. With manual data filtering, the present study explores the best use of social media data for the practical level through two case studies. They demonstrate that situation awareness and passive hotline are promising directions to be pursued in practical flood management. Future research topics including data fusion, data assimilation, model development, and data veracity, are envisioned and discussed at the end of the paper.

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